Predicting search time in visually cluttered scenes using the fuzzy logic approach

Thomas J. Meitzler [a], Euijung Sohn [a], Harpreet Singh [b], Abdelakrim Elgarhi [b], and Deok H. Nam[b]

[a] US Army Tank-automotive and Armaments Command

Research, Development and Engineering Center (TARDEC)

Warren, MI

[b] Wayne State University

Electrical and Computer Engineering Department

Detroit, MI

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ABSTRACT

The mean search time of observers searching for targets in visual scenes with clutter is computed using the Fuzzy Logic Approach (FLA). The FLA is presented as a robust method for the computation of search times and or probabilities of detection for signature management decisions. The Mamdani/Assilian and Sugeno models have been investigated and are compared. The Search_2 data set from TNO is used to build and validate the fuzzy logic model for detection. The input parameters are the: local luminance, range, aspect, width, wavelet edge points and the single output is search time. The Mamdani/Assilian model gave predicted mean search times for data not used in the training set that had a 0.957 correlation to the field search times. The data set is reduced using a clustering method then modeled using the FLA and results are compared to experiment.

[1] For further information contact:
T.J.M. (correspondence): Email: meitzlet@tacom.army.mil; Telephone: (810)574-5405; Fax (810)574-6145

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1. INTRODUCTION

It has been three decades since Prof. L. A. Zadeh first proposed fuzzy set theory (logic) [1]. Following Mamdani and Assilian's pioneering work in applying the fuzzy logic approach to a steam plant in 1974 [2], the FLA has been finding a rapidly growing number of applications. These applications include, transportation (subways, helicopters, elevators, traffic control, and air control for highway tunnels), automobiles (engines, brakes, transmission and cruise control systems), washing machines, dryers, refrigerators, vacuum cleaners, TVs, VCRs, video cameras, and other industries including steel, chemical, power generation, aerospace, medical diagnosis systems, information technology, decision support and data analysis [3, 4, 5, 6, 7].

Although fuzzy logic can encode expert knowledge directly and easily using rules with linguistic labels, it usually takes some time to design and adjust the membership functions, which quantitatively define these linguistic labels. Neural network learning techniques can, in some cases, automate this process and substantially reduce development time. To enable a system to deal with cognitive uncertainties in a manner more like humans, researchers have incorporated the concept of fuzzy logic into the neural network modeling approach. The integration of these two techniques yields the Neuro-Fuzzy Approach (NFA) [8]. The NFA has potential to capture the benefits of both the fuzzy and the neural network methods into a single model. Target acquisition models, based on the theory of signal detection or the emulation of human early vision, are not mature enough to robustly model, from a first principal approach without any laboratory calibration, the human detection of targets in cluttered scenes. This is because our awareness of the visual world is a result of the perception, not merely detection, of the spatio-temporal, spectra-photometric stimuli that is transmitted onto the photoreceptors on the retina [8]. The computational processes involved with perceptual vision can be considered as the process of linking generalized ideas, such as clutter or edge metrics [10], to retinal early vision data [9]. From a system theoretic point of view, perceptual vision involves the mapping of early vision data into one or more concepts, and then inferring a meaning of the data based on prior experience and knowledge. The authors think that the methods of fuzzy and neuro-fuzzy systems provide a robust alternative to complex models for predicting observed search times and detection probabilities for the vehicles in cluttered scenes that are typically modeled by defense department scientists. The fuzzy logic approaches have been used to calculate the search time of vehicles in different visual scenes within the commercially available MATLAB Fuzzy Logic Toolbox. [1]

2. FUZZY MODELS AND WAVELETS

Fuzzy modeling of systems is an approach, which describes complex system behavior, based on fuzzy logic with fuzzy predicates using a descriptive language. Fuzzy logic models basically fall into two fundamentally different categories, which differ in their ability to represent different types of information. The first category includes linguistic models that are based on a collection of If-Then rules with vague predicates and use fuzzy reasoning. One of these reasoning mechanisms is based on the Mamdani and Assilian fuzzy inference method. Within this method, a scientist can design the membership functions manually and the output membership functions are continuous. The second method of fuzzy inference is based on the Takagi-Sugeno-Kang , or simply Sugeno's method. In the Sugeno method the membership functions are linear or constant. For a review of these methods as applied to target acquisition modeling see [11,12].

The method of using wavelets to compute edge points, which are then used with fuzzy logic to compute the search time or the probability of detection, is derived from the elegant technique of Mallat and Zhong [15]. In [15] a derivation is made of 1- and 2-D wavelet transforms using a smoothing function, $\theta(x)$, that is a Gaussian. The integral of the function equals unity and the integral also converges to zero at infinity. We define the first- and second-order derivative of $\theta(x)$,

$$\psi^a(x) = \frac{d\theta(x)}{dx} \ \ and \ \ \psi^b(x) = \frac{d^2\theta(x)}{dx^2}. \tag{1}$$

By definition the functions $\psi^a(x)$ and $\psi^b(x)$ can be considered as wavelets because their integral is equal to zero. The following subscript 's' will be denoted as the scale factor,

$$\varepsilon_s(x) = \frac{1}{s}\varepsilon\left(\frac{x}{s}\right) \qquad (2)$$

Following standard methods, the wavelet transform is calculated by convolving a dilated wavelet with the original signal. The wavelet transform of a function f(x) at the scale s and position x, calculated with respect to the wavelet $\psi^a(x)$, is defined in [15] as,

$$W_s^a f(x) = f * \psi_s^a(x). \qquad (3)$$

Similarly, the transform with respect to $\psi^b(x)$ is,

$$W_s^b f(x) = f * \psi_s^b(x). \qquad (4)$$

The above wavelet transforms are the first and second derivative of the signal smoothed at the scale or resolution level *s*. Substituting into (3) and (4) equation (2) for the 1-D case, Mallat then derives a 2-D expression for the wavelet transform of a function or image,

$$\begin{pmatrix} W_s^1 f(x,y) \\ W_s^2 f(x,y) \end{pmatrix} = s\begin{pmatrix} \frac{\partial}{\partial x}(f*\theta_s)(x,y) \\ \frac{\partial}{\partial y}(f*\theta_s)(x,y) \end{pmatrix} = s\vec{\nabla}(f*\theta_s)(x,y). \qquad (5)$$

The above wavelet transform definitions in (5) are important for a wavelet based clutter metric because they essentially define edge detectors that are used in the vision science community. For more discussion on this topic see ref. [16]. An implementation of eq. (5) in the program XWAVE was used to compute edge points.

3. IMPLEMENTATION

The Fuzzy Inference System (FIS) that models the relationships between the various input variables that affect the determination of the search time is done specifically for this data set. The predicted search time for target detection can be determined with the FLA using input target metrics for the images from the Search_2 database [18]. Sample images are shown below in Fig.'s 1 through 6. The input variables were; distance from the target to the observer (km), the aspect angle of the vehicle relative to the observer (deg), the target height (pixels) and the target area ($pixels^2$), target and the local background luminance (cd/m^2), and the wavelet determined edge points of the scene as a measure of clutter. The one output parameter is the search time. There were a total of 44 digitized color images along with the associated target and background metrics for the targets in each picture. 22 images are used for training and 22 are used for testing. Both the Mamdani and Sugeno type FIS methods are used and compared. The authors constructed the FIS's to predict search times using the MATLAB Fuzzy Logic Toolbox [13].

For implementation we used the ANFIS (Adaptive Neurofuzzy Inference System) in the Fuzzy Logic Toolbox of MATLAB. The steps of ANFIS are summarized below;

1. *Load data sets such as checking data and training data*.

   The checking data will help for the model validation. For example, if we have an N by M matrix as an original data set. N will be the number of the observations of the data set and (M – 1) will be the number of input parameters. Finally, the last column of N by M matrix will be the output parameter for the system. To decide the training data, select n (N > n) rows and M columns from the original data matrix (N by M matrix). The remainder part of N by M matrix will be used as the checking data such as an (N – n) by M matrix. The output matrix for the training data will be n by 1 matrix and the output matrix for the checking data will be (N – n) by 1 matrix.

2. *Initialize and generate the fuzzy inference system.*

   Choose either grid the partition, that is the default partitioning method, or a clustering technique.

   (a) If we choose the clustering technique, then decide the parameters for Subtractive clustering method such as the range of influence, squash factor, accept ratio, and rejection ratio. Generally, the values of parameters will be given as default values. In addition, the Gaussian Bell shape membership function will be chosen as a default membership function for each input parameter.

   (b) If you choose the non-clustering method, which is about the grid partition method, you have to decide the number of membership functions for each input variable. After that, specify your own membership functions such as triangular, trapezoid, Gaussian bell shape, Gaussian function shape, Gaussian 2 function shape, Pie shape, and sigmoid function shapes. For the output membership functions, there are only two types of functions such as constant and linear since ANFIS only operates on Sugeno-type systems.

   (c) Simultaneously, the number of membership functions and the types of membership functions will generate the rules of the neurofuzzy system.

3. *Select the ANFIS parameter optimization method for the neurofuzzy inference system.* There are two options such as **hybrid** method, which is the default, mixed least squares and backpropagation gradient descent method, and **backpropa**, that is the backpropagation only. The Error Tolerance is used to create a stop after training data error remains with in this tolerance. For the best result, leave 0 if you do not know how your training error is going to behave.

4. *Set the number of epochs* for training the system.

5. *Start the training* for the neurofuzzy inference system.

6. After training neurofuzzy inference system, two lines of graphs will be created by choosing the model parameters associated with the minimum checking error from checking data options. You can view the rules of the neurofuzzy systems from the "View" of menu bar.
7. *Test your data* against the trained neurofuzzy system

   To test your neurofuzzy system against the checking data, select checking data in the Test FIS portion of the graphic user interface and choose Test Now.

3.1 SUMMARY OF ANFIS

1. Load data sets such as training data and checking data.
2. Initialize and generate the FIS selecting one the partition methods and specifying the number of membership functions and the shapes of membership functions of input parameters and output parameter.
3. Select the ANFIS parameter optimization method for the neurofuzzy inference system.
4. Decide the number of training epochs for the FIS.
5. Start the training for the FIS.
6. Test the trained FIS against testing data such as checking data.

3.2 RELATED FUNCTIONS FROM MATLAB

The following are some of the MATLAB Fuzzy Logic Toolbox commands used in the implementation of ANFIS.

anfisedit

  To create, train, and test a Sugeno fuzzy system

genfis1

Generates a FIS structure from a training data set, data, using a grid partition on the data (no clustering for grid partitioning)

genfis2

Generate an FIS structure from data using subtractive clustering

mfedit

Membership function editor

ruleview

Rule viewer and fuzzy inference diagram

ruleedit

Modify the rules of a FIS structure stored in a file

surfview

Output surface viewer

3.3 WAVELET EDGE ENHANCEMENT COMMANDS

Additionally, commands used to compute the number of edge points that is used as the last input parameter, input 8 (See Table l) is summarized as follows;

- Read the input 256 X 256 element matrix which supports a discrete 2-D image f(x,y)
- Determine the number of pixels on the target length and height
- The cell size then equals twice the length of the maximum target dimension
- Divide the image matrix into the maximum number of cells allowed
- Take the wavelet transform of each cell using (5) at a certain resolution level
- Set the threshold, here chosen as zero
- Determine the number of edge points in each cell along with the number of pixels
- Find the edge density from the number of edge points divided by the total number of pixels

- Iterate s, the level of wavelet in the analysis
- Find the edge density of the image as before and compute the WPOE clutter metric
- Apply a calibration scale factor based on experiment
- Find the probability of detection (Pd) for the target in the scene.

Search_2 Sample Visual Images

Fig. 1

Fig. 2

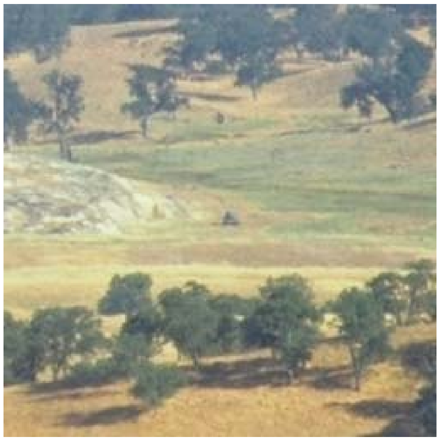

Fig. 3

Fig. 4

Fig. 5

Fig. 6

Table I below lists the metrics used in the trials. The table entries, all except ‘Edge points’, were provided with the Search_2 data set. The entries are; target type number, distance from target to sensor, the absolute value of the sin of the aspect angle of the vehicle relative to the observer, the height of the target in pixels, the area of the target in pixels, the target luminance, the darkest part of the target luminance, the surrounding area average luminance, edge points and the mean search time in seconds. The edge points were found using a wavelet program to compute the number of wavelet edge points over the whole image to give a measure of the clutter in the image.

TABLE I Metrics for FIS construction

TARGET NO	**distance**	**aspect**	**vert**	**area**	**target lum**	**Dark area lum**	**Surround lum**	**Edgepts**	**SEARCH TIME**
type	m	ass(sin)	pixels	*(pixels)*	scene	dark	grass	**pts**	search time(s)
1	4007	0.707	10	141	14	17	29	9571	14.6
1	2998	0.819	11	225	21	10	27	8927	15.2
2	3974	0.707	13	173	20	24	28	9138	12.4
3	5377	0.052	5	49	18	23	30	8970	29.8
2	1013	0.515	50	2708	19	5	34	8706	2.8
4	3052	0.000	11	100	12	18	30	8755	6.4
5	5188	0.407	9	76	18	23	28	9053	26.7
6	3679	0.122	10	96	12	20	26	8620	10.0
2	860	0.995	54	3425	9	1.5	40	8961	2.7
4	1951	0.848	16	332	15	11	27	8572	2.8
3	3992	0.788	11	154	20	19	26	9194	11.9
6	1041	0.743	24	1645	11	4	35	9074	2.5
7	2145	0.978	17	553	8	5	18	8280	3.7

3	1998	0.755	19	659	20	10	22	8739	8.1
2	4410	0.000	11	101	22	18	29	9404	12.4
1	2893	0.423	16	320	12	7	23	8670	2.5
5	1933	0.978	13	368	15	12	23	8606	4.8
1	1850	0.961	28	876	3	4	9	8464	2.8
8	1045	0.087	26	985	19	10	12	8613	12.3
2	1933	0.946	22	867	16	11	27	8376	2.8
7	4206	0.000	9	79	26	29	38	9506	15.1
1	5722	0.883	7	73	38	40	46	9044	25.6
4	4920	0.423	8	61	20	21	36	8618	12.1
6	4206	0.809	9	142	18	12	21	9152	8.0
5	2348	0.940	9	198	18	21	30	8504	5.5
1	3992	0.875	11	217	15	14	26	9078	7.8
9	4410	0.956	11	247	16	8	19	9397	9.6
8	2321	0.829	15	458	22	21	47	8365	5.1
5	3661	0.755	9	84	17	25	23	8807	7.5
3	3670	0.000	13	192	14	15	27	8483	6.1
7	1671	1.000	19	893	15	13	31	8959	3.5
4	4345	0.809	8	63	15	12	20	9021	12.3
2	3662	0.574	10	203	26	25	44	8702	5.4
5	633	0.707	50	4403	20	5	39	8741	2.5
3	492	0.070	57	3045	20	16	23	8992	2.2
4	1497	0.777	16	560	10	7	20	9014	5.8
5	1041	0.999	33	1613	17	5	32	8486	2.6
1	2891	0.985	19	486	12	12	35	9021	12.1
7	5147	0.934	5	81	18	27	34	9075	34.9
6	1648	0.588	18	648	23	7	37	9070	2.7
8	948	0.731	35	1463	18	5	38	8790	3.7
7	3662	0.407	12	188	19	25	39	8524	5.8
6	2900	0.000	17	340	20	10	49	8791	4.1
2	5136	0.000	10	79	25	16	27	8941	10.6

Below in Fig. 7 is the Mamdani type FIS with the input parameters mentioned above and the search time as the single output. Fig. 8 is the firing array for the various membership functions using the Mandani approach.

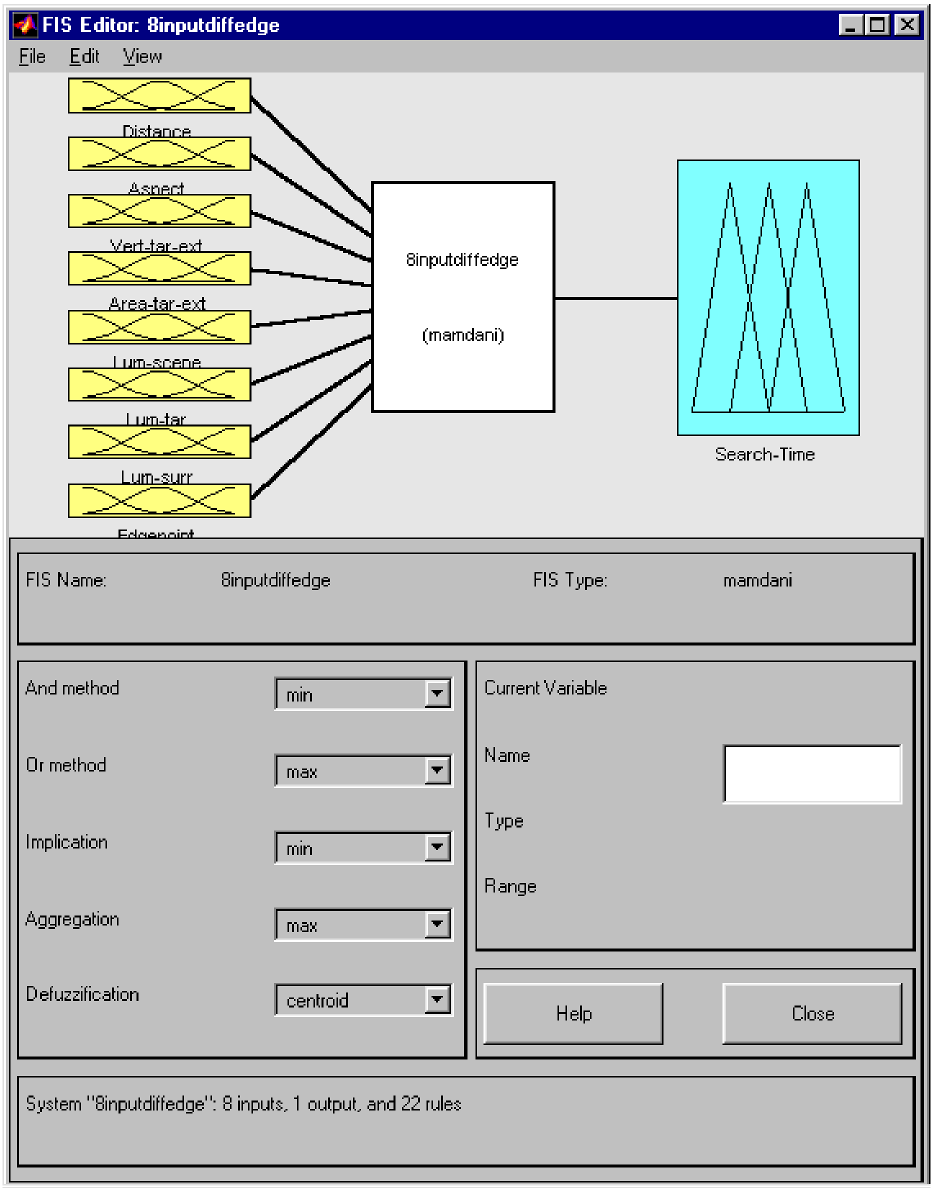

Fig. 7. Mandami Fuzzy Logic Identification System for computing visual search times

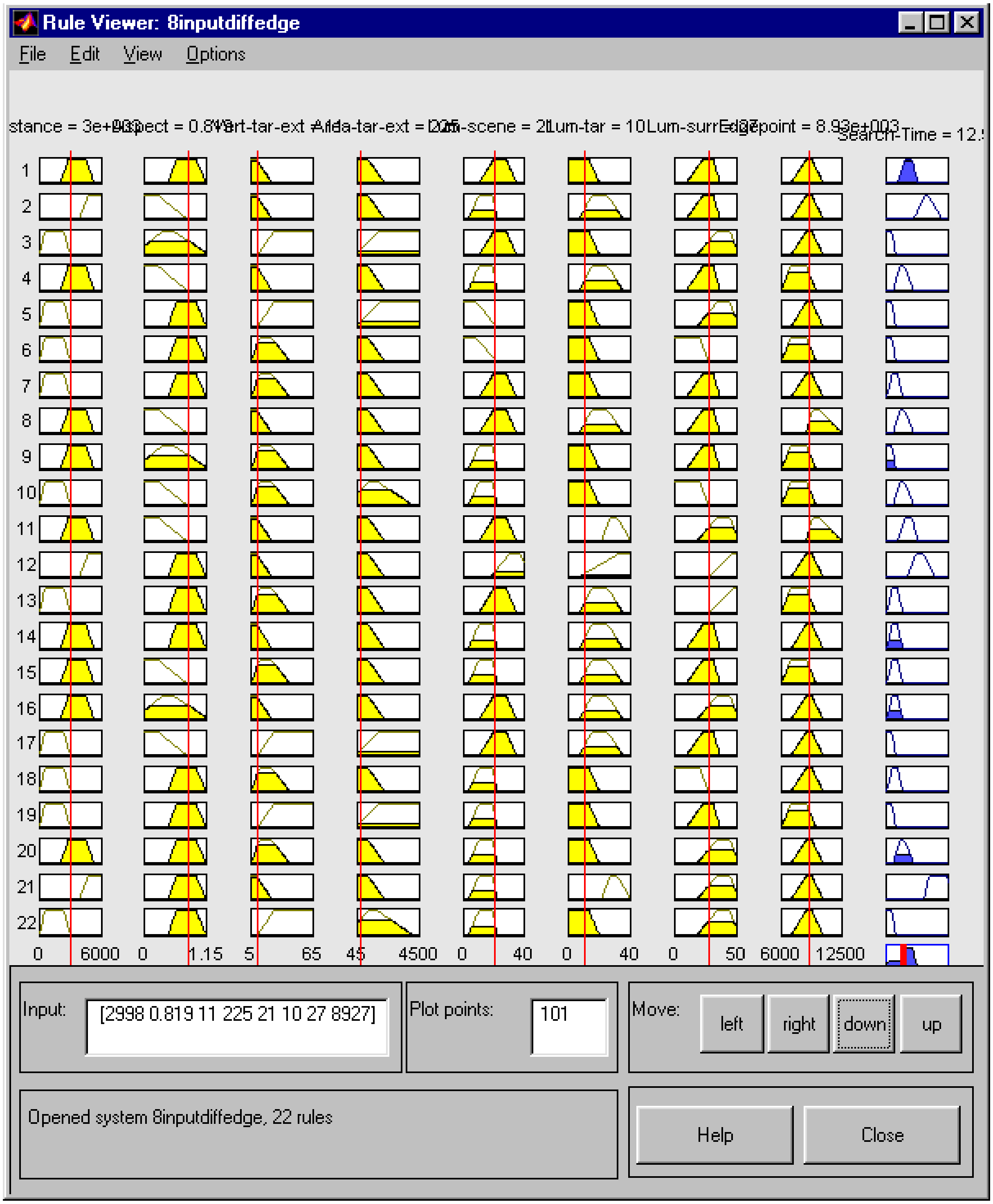

Fig. 8 Firing diagrams for the Mamdani FIS to predict search times

4. RESULTS

Fig. 9 shows the correlation of laboratory search times to FLA predicted search times using the Mamdani approach and membership functions we designed. The correlation of model predicted search times to experimental search times was 0.957. Fig. 10 is the output of the ANFIS model of the data, which gave a 0.60 correlation to the data. We also tried using the Mamdani FIS, with the 0.957 correlation to experiment, on another data set of visual imagery [14]. The FIS from one data set can be used to model another data set, if and only if, the metrics used to describe the various data sets are similar.

These results are indicative of the power of using the FLA to model highly complex data, for which there would be many interrelated equations if one tried to model the detection problem in the conventional standard algorithm based method.

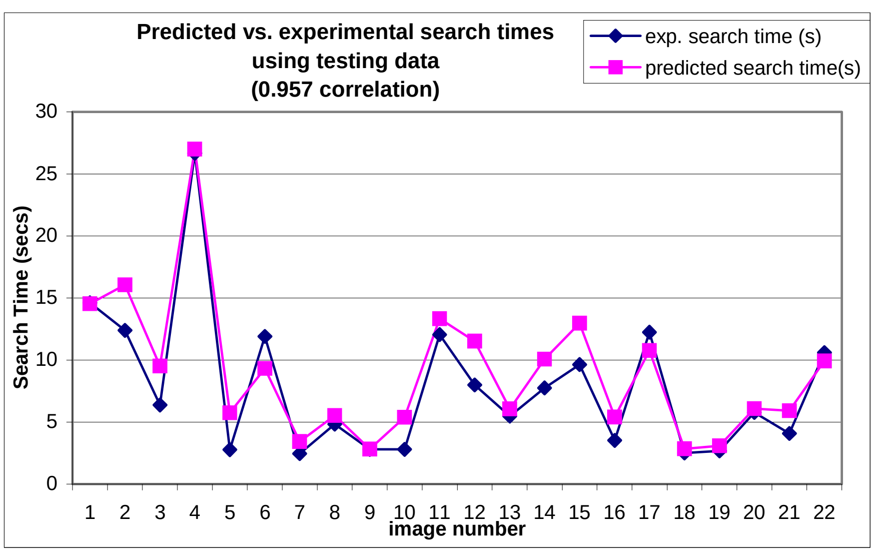

Fig. 9 Graph of search times from Mamdani FLA model and the laboratory

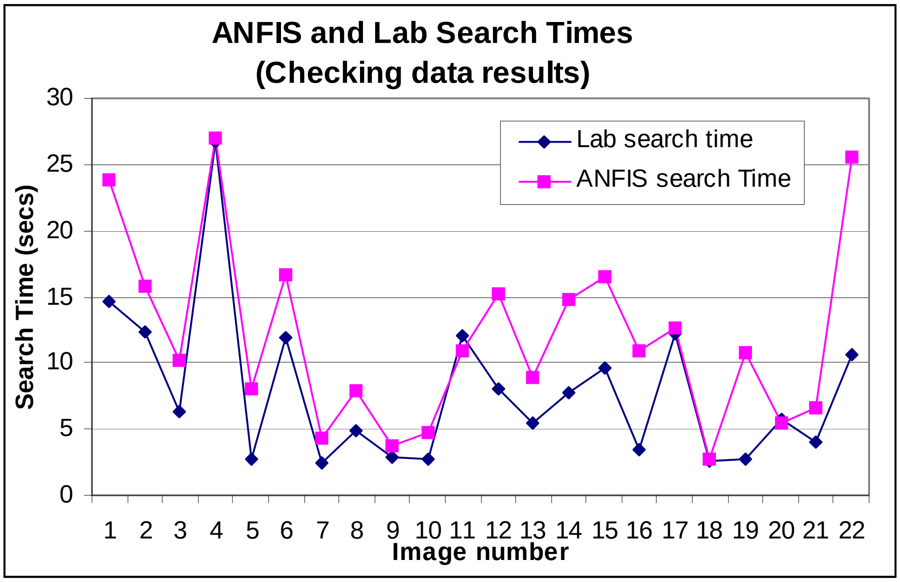

Fig. 10 Chart showing the comparison of experimental search times to ANFIS FLA predicted search times

Clustering was also used to model the visual metrics and responses. For a large data set, it will be desirable to reduce the number of input vectors to a small number to reduce the number of rules and membership functions that need to be constructed. Clustering was used to obtain the means of the 7 input vectors. The center of the clusters was used in the construction of the membership functions. The correlation results are shown below in Table 2. Clusters were made of 15, 18 and 20 data points. The FLA with clustering was used to predict search time for the 22 points not used in obtaining the clusters and for the entire data set of 44 images.

TABLE 2 System Evaluation Using Cluster Centers

Cluster	**Correlation for 22 points which are not used for clustering.**	**Correlation for 44 points**
fcm15	0.83	0.85
f18	0.75	0.82
fc20	0.82	0.88

It is expected that increasing the number of cluster centers and the number of rules will improve the correlation. This is not the case when the number of clusters was increased from 15 to 18. The reason for this is due to the random operations used in clusters' center calculations. In other words, if we started from another clusters' center we may get better correlation. We used the cluster centers as the centers of membership functions, but chose initial values for the width. We can then tune the width manually to increase the correlation. It is clear that there needs to be an objective algorithm or technique to tune the width of the membership functions as ANFIS does. Below in Fig. 11 is a snapshot of the result of clustering the input variable distance over 15 cluster means.

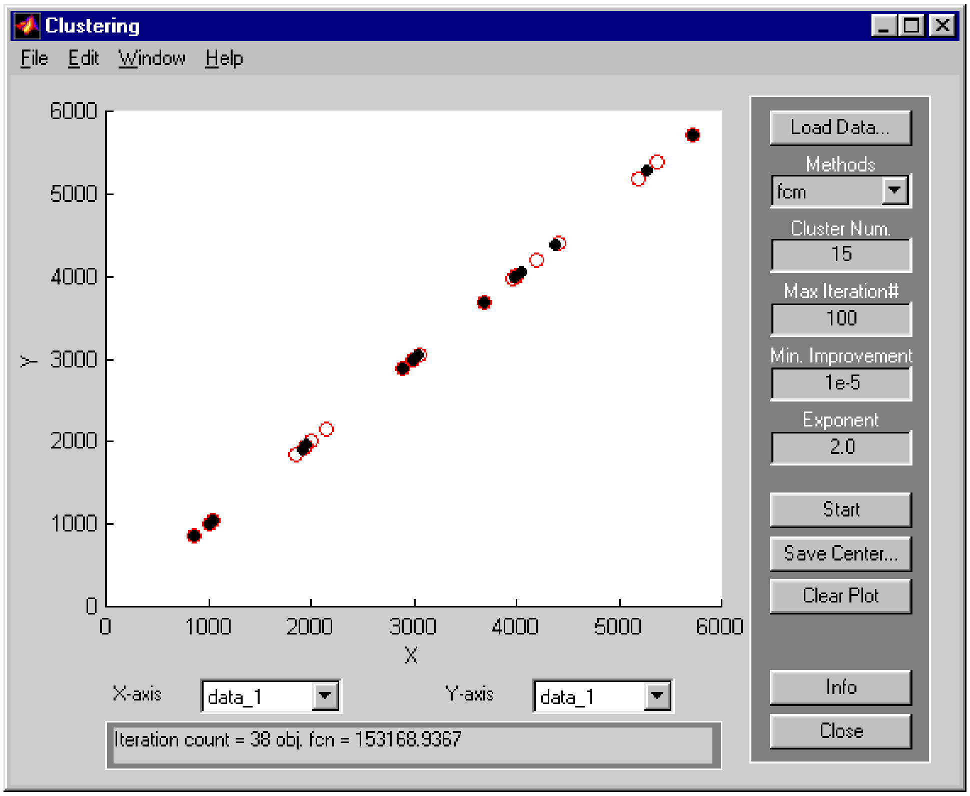

Fig. 11 Clustering results using 15 clusters

5. CONCLUSION

Two fuzzy models have been used; the Mamdani and Sugeno models. With the Mamdani method, a scientist can design the membership functions manually and the output membership functions are continuous. In the Sugeno method the membership functions are linear or constant. For a review of these methods as applied to target acquisition modeling see [11,12]. This application of the FLA involved pictures, metrics, and experimental search times of images in the visual band. Future work will involve the application of the FLA to predict the Pd's of ***moving*** targets in visual and infrared cluttered scenes for military and commercial applications. Clustering of the input data was explored as a means to reduce the number of input vectors and membership functions. For large data sets, a saving of computational time and effort should be realized using this approach.

In conclusion, as an interpolating model, the FLA yields very satisfactorily results, 0.96 correlation of laboratory or field data to model predicted data, and requires a fraction of the effort that goes into traditional algorithm based techniques of modeling target acquisition probabilities and search times. We expect that the fuzzy modeling approach could be used in the existing statistical decision theory modules of target acquisition models for any spectral band. The robustness of the model is a function of the data set used to build it. If an FLA model could be constructed using several data sets and types of vehicles the extrapolating power of the model would be increased. Detection prediction would also be enhanced if metrics essential to quantifying detection were included into the design of the membership functions. Wavelet derived edge points were used by the authors in the model discussed in this paper as such a metric, but, there are others that could be used. Additionally, if a relative metric is used as one of the input vectors, a determination could be made as to which of the metrics is contributing the most weight to the final detection probability value [17].

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Biographies:

Dr. Thomas Meitzler received his B.S. and M.S. in Physics from Eastern Michigan University and a Ph.D. in Electrical Engineering from Wayne State University in Detroit, Michigan. His Ph.D. thesis was “Modern Methods of Computing the Probability of Detection in Cluttered Scenes.” He has co-authored several papers in the fields of target detection, infrared and visual system simulation, fuzzy logic, and wavelets. He has held adjunct teaching positions at The University of Michigan-Dearborn in both the physical science and electrical and computer engineering departments.

During the time from 1988 to present he has been a research scientist at the U.S. Army TACOM Research and Engineering Center (TARDEC), Survivability Technology Center. He has been involved with the validation, verification, and development of electro-optical, visual detection models and atmospheric propagation computer programs. He directed the construction of a visual perception laboratory at TARDEC for the testing of civilian and military ground systems. Dr. Meitzler was a recipient of the 1995 Army Research & Development Award for the Computational Vision Model Development for Dual-Use Applications.

Mrs. Euijung Sohn was born at Suwon, Korea in 1966. She attended elementary and high school in Korea and immigrated to the U.S. of America in 1985. She finished her high school degree in Park Ridge, IL. She studied at the University of Illinois and got her B.S. degree in Electrical Engineering in 1991. After her graduation, Mrs. Sohn was hired in Simulation department in US Army Tank Automotive Command in 1991. She was involved in the various type of terrain simulation with the six-degree of freedom moving simulator and analyzed the results from many test sensors. Mrs. Sohn has worked as a research engineer from 1992 to present in the Survivability Center. She has been involved in the validation, and verification of thermal and visual detection models and atmospheric propagation studies. Mrs. Sohn is now involved in planing, testing, and analyzing visual perception test of military ground vehicles and also commercial vehicles. She has developed some fuzzy models based on the Matlab application predicting the probability of detection based on the detection value from the perception test data. Mrs. Sohn has co-authored several technical papers in the area of infrared and visual system simulations and target detection. Mrs. Sohn was a recipient of the 1995 Army Research & Development Award for the Computational Vision Model Development for Dual-Use Applications.

Professor Harpreet Singh received his B.Sc. in Engineering. from Punjabi University in 1963. He received a Ph.D. in Electrical Engineering from the University of Roorkee, India in 1971. He was with the Electronics and Engineering dept. of Roorkee from 1963 to 1981. He developed a postgraduate program in computer engineering at the Univ. of Roorkee. He was the winner of the Khosla Award (highest) in 1971 from the Univ. of Roorke. He joined WSU in 1981 and is presently serving as a professor in this Univ. He has over 250 publications in international journals and conferences. He has also served as the Associate chairman of the dept. of Electrical and Computer Engineering for several years. His current areas of interest are, computer vision and target detection, system theory, fuzzy and neural networks, and software engineering.